TACIT COLLUSION AND MOVIE RELEASE DATES

by

BRYAN ALAN LAGALO

(Under the Direction of David Kamerschen)

ABSTRACT

Movie studios rarely release two films with large budgets, wide theater releases, or similar genres on the same weekend. One possible explanation is that studios tacitly collude by spacing out movie release dates. This type of collusion can be categorized as an alternating-periods monopoly (APM), where firms take turns as a monopolist rather than collectively acting as a monopolist each period. Using duration analysis and a Weibull hazard function, I find evidence that, during the sample period 2005-2009, studios spaced-out releases of films costing more than $100 million, or that were released in more than 3,250 theaters, sequels, similar genres, or assigned a G-rating.

INDEX WORDS: Tacit collusion, Alternating-periods monopoly, Movie industry, Weibull hazard function, Duration analysis

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DEDICATION

This thesis is dedicated to Professor Fred Bateman who taught me the importance of economic history. His courses significantly increased my teachable knowledge in the fields of U.S. history and economics.

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CHAPTER 1

INTRODUCTION

On a typical weekend, movie studios release four or five new films. Usually, each release has a different budget size and genre (Einav, 2010): rarely are two big-budget films, or two films of similar genres, released on the same weekend. This pattern suggests studios may tacitly collude by planning releases. Einav and Orback (2007) show that release dates are crucial to films' financial performance. Aside from quality, release dates are the main form of competition in the movie industry since ticket prices are largely fixed over the year and across films.

For example, the big-budget, comic-book movie *Iron Man* was released two months before *The Dark Knight*. *Iron Man's* primary competitors during its opening weekend were *Nightmare on Elm Street* (a horror film) and *Date Night* (a romantic comedy); *The Dark Knight*, in turn, faced *Mamma Mia* (a musical) as its main opening weekend competitor. Another example involves the first movie in the *Twilight* series. Originally, the film's release date in 2008 was scheduled for more than a month after the scheduled release of the movie *Harry Potter and the Half Blood Prince* during the weekend before Thanksgiving. The day after an announcement was made that the *Harry Potter* sequel would be moving to the following July, *Twilight's* studio announced a change to the earlier release date of Thanksgiving (Adler, 2008).

Zillante (2007, p. 1) provides an example of explicit collusion in the movie industry. In 2002, two films starring Leonardo DiCaprio were set to be released. The studios Miramax and Dreamworks, respectively, planned to release *Gangs of New York* and *Catch Me if You Can* on

Christmas Day. However, Miramax moved *Gangs of New York* to an earlier release date of December 20th after two top studio managers met with each other. Laura Holson reports:

> Jeffrey Katzenberg, a Dream-Works co-founder, who is also a friend of Mr. (Harvey) Weinstein, said in an interview today that he had breakfast with Mr. Weinstein last week in New York to discuss their respective movies' release dates and joked that they settled their differences after the two ate waffles, and later "stayed up late telling manly stories." All kidding aside, he agreed that the decision was based more on economics than breakfast food and bonding. "He and I had many conversations about why releasing the movies on the same day was in none of our interests," Mr. Katzenberg said. "It was an uncomfortable situation as both companies have a big investment in Leo DiCaprio." (New York Times, pg. C1, October 11, 2002)

Managers of the various studios thus appear to time releases to avoid direct competition between similar films and instead, release movies with different target audiences on the same weekend.

While the evidence above is merely anecdotal, such examples provide a motivation to investigate the possibility of tacit collusion among studios regarding the timing of movie releases. The goal of this thesis is to determine whether studios avoided competition by spacing out movie releases based on similar characteristics such as budget size, the number of opening theaters, MPAA rating, sequels, and movie genres. Using duration analysis and a Weibull hazard function, I examine whether studios timed releases by spacing out similar films.

I find evidence that during the sample period of 2005-2009 studios avoided competition by spacing out releases of similar films. In particular, studios spaced-out releases of films costing more than $100 million, or were released in more than 3,250 theaters, sequels, or assigned a G-rating. Not surprisingly, a robust test indicates that each studio spaced-out its own releases. Finally, I find that the studios spaced-out releases of the following film genres: animation, fantasy, history, horror, mystery, sport, action-comedy, adventure-action, adventure-animation, drama-action, drama-comedy, drama-crime, family-fantasy, horror-thriller, romance-comedy, and romance-drama.

CHAPTER 2

LITERATURE REVIEW

Tirole et al. (2007) provide an excellent summary of collusion. The authors state that *tacit* collusion

> ...in particular need involve no communication between the parties. It is referred to as tacit collusion only because the outcome (in terms of prices set or quantities produced, for example) may well resemble that of explicit collusion or even of an official cartel. …[and] there is more scope for collusion when the same firms compete repeatedly (2007, p. 4 and 19).

Since ticket prices are largely fixed over the year and across films, release dates are the main form of competition aside from quality in the movie industry. Studios have an incentive to tacitly collude by spacing out movie releases to increase the financial performance of their films.

Amelio and Biancini (2010) set up a theoretical model for what they define as an alternating-monopoly strategy, and compare it to a benchmark case of a market-sharing strategy. In a market-sharing strategy, firms share monopoly profits equally each period. In an alternating-monopoly strategy, firms take turns as single monopolists during a particular period; one firm is the sole producer each period and the other firms temporarily shut down.

Herings, Peeters, and Schinkel (2005) highlight an example in which Coca-Cola and PepsiCo alternated advertising campaigns:

> Dixit and Nalebuff (1991), e.g., refer to a report on "60 Minutes" that in a span of 52 weeks Coca Cola and Pepsi Cola each offered 26 weeks of price promotions between which there was not one single overlap. They calculate the probability that this would occur by luck if the two companies were acting independently and each offered 26 weeks of "couponing" as 1/495,918,532,948,104, which they conclude is strong statistical evidence for collusive behavior (Dixit and Nalebuff, p. 193).

The likely purpose of this alternating-monopoly strategy was to take turns boosting sales without directly competing in a particular week.

Amelio and Biancini (2010) list three reasons why firms may favor an alternating-monopoly strategy over a market-sharing strategy. The first reason is the ability to observe firms' prices. Under an alternating-monopoly strategy, cheating occurs if a firm does not "wait its turn," whereas under a market-sharing strategy a firm may cheat by lowering its price, making cheating more difficult to detect. Second, advertising may encourage an alternating-monopoly strategy because it provides output and release information to the competing firms. Finally, demand uncertainties create a larger incentive to cheat under a market-sharing strategy. During a high-demand period, firms under a market-sharing strategy have a strong incentive to cheat because the firms are unaware of when another high-demand period will occur. However, under an alternating-monopoly strategy if firm A cheats by releasing out of turn the other firms will likely punish firm A by collectively increasing releases during firm A's turn.

An alternating-monopoly strategy may be preferred to a market-sharing strategy in the film industry for several reasons. First, since movie ticket prices are relatively constant, studios cannot mimic the traditional collusively induced monopoly price and collectively produced monopoly output under a market-sharing strategy. Second, studios are able to use large advertising campaigns to signal release dates to each other. Millions of dollars of sunk costs in advertising may also signal the credibility and commitment to an announced release date. If studios decide to tacitly (or explicitly) collude, then advertising reduces asymmetric information and monitoring costs. Finally, the movie industry follows a very predictable seasonal pattern. Demand is high on most major holidays and during the summer months, and demand is low in January and September. Studios can take turns releasing their best films in high-demand periods and their worst films in low-demand periods. For example, highly anticipated sequels are usually released during the summer and a week or two before Thanksgiving. On the other hand, low-quality movies are often released in the months January and September. For example, the films *Season of the Witch*, *Bangkok Dangerous*, and *The Wicker Man* were released in January or September and received Metacritic scores (a proxy for quality) of 28, 24, and 36 out of 100.

Zillante (2005) describes alternating-periods monopoly (APM) in a manner similar to the alternating-monopoly strategy discussed in Amelio and Biancini (2010). Zillante tests for APM empirically in the baseball-card market by employing duration analysis with a hazard function specified by a Weibull distribution. The author finds no evidence of a collusive outcome in the baseball-card market.

Zillante mentions several additional factors that make APM more attractive as a collusive strategy than a market-sharing strategy. Higher innovation costs, the cost necessary to develop and market a new product, encourage an APM strategy. Under a market-sharing strategy, firms that introduce a product in each period must pay an innovation cost in every period, but under APM a firm pays the cost only in the rotating periods when the firm produces as the monopolist. Production technology may also play a role. Firms capable of halting production for a few periods, and then quickly restarting production during its period as the monopolist, will be more capable of engaging in APM.

Zillante also argues that APM may actually increase welfare, for two reasons. First, it can eliminate wasteful duplicate innovation costs described above. Second, consumers may prefer a steady stream of new products instead of a cluster of new products every few periods. The concept of "newness" may be important for buyers. A movie studio is not required to pay for innovation costs each period (for example, every week); it simply incurs the production costs of a movie and then can store the finished product for future release. However, this provides studios with the ability to start and stop production easily and facilitates the use of APM as a collusive strategy. In addition, consumer welfare might actually be higher under a scenario in which studios space out movie releases instead of clustering similar films on the same weekend or holiday. Consumers may prefer to attend one movie every week for four weeks rather than watching four movies once a month in a single week. Einav (2007, p. 135) uses evidence from focus-group participants to confirm the importance of "newness" in the movie industry, and finds that "…most people prefer watching a movie earlier in its release." For example, the highly anticipated film *The Dark Knight* grossed $18.5 million in ticket sales from the midnight screenings alone before its opening release date (Wortham, 2008). In addition, the first week of a film's release typically brings in 40% of sales, and well over 50% by the second week (Einav, 2007).

Einav (2010) models the release-timing game played by movie studios. Since price plays only a small role in the industry, studios compete on quality and on the timing of releases during high-demand periods. Studios announce movies twelve to eighteen months before the actual release date in an attempt to soften potential competition. The author concludes that studios cluster film releases; "too many" high-quality movies are released during holidays when demand is high. Einav argues that studios could earn higher profits from spacing out releases by a few weeks before or after a holiday.

This paper builds upon the research done by Einav (2010) in several important ways. First, Einav restricts his sample to films released in more than 600 theaters with high weekly ticket sales, and only those released during four five-week-long periods surrounding Presidents' Day, Memorial Day, Fourth of July, and Thanksgiving. My sample does not restrict films based on opening theaters, ticket sales, or release date. Also, I examine whether studios spaced-out or clustered releases based on specific characteristics: budget size, opening theaters, MPAA rating, sequel, and genre. Second, Einav's data range over the period 1985 to 1999 and the data in this thesis span the more recent period 2005 to 2009. Using more recent data may be important because, as Einav (2010, p. 388) acknowledges,

> … [I]t should be noted that in recent years distributors started to experiment more with less traditional release decisions. After relative successful early May openings of *Gladiator* and *The Mummy Returns* in 2000 and 2001, the distributors of *Spiderman* - an anticipated blockbuster much before its actual release - decided to release it on May 3, 2002. Ten years earlier such a move would have been unheard of.

Finally, Einav uses a nested logit procedure, while I model the timing of movie releases using duration analysis. Einav (2010, p. 388) admits:

> Third, as is well known, the nested logit specification used to obtain the demand estimates assumes that all movies are equally good substitutes of each other, proportional to their market shares. If the top movies every season are of different genres, the revenues of these movies may be less affected by clustering with other movies.

This calls into question Einav's conclusion that studios cluster releases since he does not control for genre or MPAA ratings, and his results do not provide evidence about the timing of releases around weeks in the year other than those to which he restricts his sample.

CHAPTER 3

DATA DESCRIPTION

The data contain 755 observations between the years 2005-2009. The unit of observation is a particular movie released during these years. Table 1 and Table 2 provide summary statistics for the entire sample. The data were collected from the websites Box Office Mojo, The Numbers, Metacritic, and the Internet Movie Database (IMDb).

The sample contains data on each film's ticket sales in the U.S. (U.S. box office) and the cost of production (budget). Budget data were only available for 707 out of the 755 films. I restrict the sample to films that have a budget size over $1 million, because most films that cost less than $1 million have missing data on other variables. For the same reason, I exclude documentaries and foreign films from the sample.

Table 1: Summary Statistics of Continuous Variables. Notes: The total sample size is 755. Budget data are only available for 707 films. Budget Size is the cost of a film. Metacritic Score is a proxy for quality, and ranges from 0 to 100. Opening Theaters is the film's total number of theaters the first weekend of release. Rate of Return = (USBO-Budget)/Budget

Variable	Mean	Std. Dev.	Min.	Max.
Budget Size	$49,100,000	$47,100,000	$ 1,000,000	$425,000,000
US Box Office (USBO)	$59,600,000	$71,300,000	$ 397,641	$761,000,000
1st Weekend USBO	$17,800,000	$20,500,000	$ 51,907	$158,000,000
% USBO from 1st Weekend	33.9%		0.2%	66.4%
Rate of Return (ROR)	59.8%		-97.7%	1950%
Metacritic Score	49.4	16.9	7	96
Opening Theaters	2467	988	2	4366

A proxy for a film's quality is its Metacritic score. Metacritic consistently converts film reviews to a scale ranging from 0 to 100 regardless of the type of scoring system a particular critic uses (four stars or a letter grading system, for example). The attractiveness of this measure is that the website collects all available professional-critic reviews and computes a weighted average. Well-known movie critics are given larger weights than less reputable ones.

Another important variable is the number of theaters a film is released in during its first weekend. It should be noted that the number of *theaters* is usually less than the number of *screens* a film opens on because many theaters play highly anticipated films on between two and four screens. Unfortunately, data are not available on the number of screens; therefore, the number of theaters serves as a proxy for the number of screens since more theaters imply more screenings.

Table 2: Summary Statistics of Discrete Variables. Notes: G, PG, PG-13, and R are MPAA ratings. Sequel or Prequel is a dummy variable indicating if the film is a sequel, prequel, spinoff, or remake of an existing movie or television show. Holidays is a proxy for peak demand and is a dummy variable representing releases on the following holidays: Memorial Day, Independence Day, Veterans' Day, Thanksgiving, and the week between Christmas and New Year's Day. September Release and January Release are dummy variables which proxy for the lowest seasonal demand. Years 2005-2009 are year dummies for the sample.

Variable	Mean	Variable	Mean
G	3.3	Year - 2005	18.7
PG	18.9	Year - 2006	20.7
PG-13	44.4	Year - 2007	21.9
R	33.4	Year - 2008	20.5
		Year - 2009	18.3
Holiday Release	30.5		
January Release	8.2	Sequel or Prequel	19.5
September Release	8.6		

The data also include separate dummy variables for whether a film is a sequel, if it was released on a major holiday, if it was released during January, and if it was released during September. Sequel status extends to prequels, some continuation of a movie series, spinoffs, and remakes. Major holidays include Memorial Day, Independence Day, Labor Day, Thanksgiving, and the week between Christmas and New Year's Day.

Whereas holidays proxy peak demand, the months of January and September represent trough demand. Historically, movie ticket sales are generally lowest in January and September. This is probably because students are returning to school from summer and winter breaks, and working adults are returning from vacations. In addition, each film is assigned a rating by the Motion Picture Association of America (MPAA). The MPAA ratings are general audience (G), parental guidance suggested (PG), parents strongly cautioned (PG-13), and restricted (R). Table 2 contains percentages based on MPAA rating, holiday release, January release, September release, sequel or prequel release, and the films released in each year of the sample period.

Finally, each film is also classified by genre using one to four dummy variables. The genres were assigned by and collected from the Internet Movie Database (IMDb). Films are categorized by one to four of the following genres: action, adventure, animation, biography, comedy, crime, drama, family, fantasy, history, horror, music, mystery, romance, science fiction, sport, thriller, war, and western. Most films in the sample were assigned three or four genres, while few films are assigned only one genre.

Table 3 provides summary statistics for each genre. The mean rate of return by genre ranged from -12% for history-based films to 144% for films with a horror theme. Over half of the genres had at least one film that earned a rate of return of -90% or worse. This means the film brought in extremely low ticket sales relative to the film's budget. In addition, the maximum rate of return of return ranged from 251% for a war themed film to 1,950% for a film categorized as a drama-comedy.

Table 3: Summary Statistics by Genre. Notes: The total sample size is 755. Budget data are only available for 707 films. The total number of films for all genres sums to a number larger than the sample size because each film is categorized by up to four genres. ROR is the rates of return. ROR = (USBO-Budget)/Budget

Genre	n	Mean ROR	Std. Dev.	Min.	Max.
Action	172	0.14	0.944	-0.92	4.80
Adventure	155	0.27	1.106	-0.98	6.49
Animation	51	0.34	0.834	-0.98	3.14
Biography	28	0.45	1.555	-0.78	6.31
Comedy	291	0.71	1.963	-0.98	19.50
Crime	130	0.54	1.605	-0.92	7.02
Drama	314	0.71	1.930	-0.93	19.50
Family	83	0.29	1.288	-0.83	7.23
Fantasy	86	0.17	0.983	-0.91	4.93
History	20	-0.12	0.910	-0.70	3.50
Horror	75	1.44	2.606	-0.84	16.41
Music	35	0.80	1.804	-0.88	6.93
Mystery	74	0.87	2.480	-0.93	16.41
Romance	122	0.79	1.479	-0.90	8.16
Science Fiction	41	0.13	0.805	-0.81	2.85
Sport	35	0.31	1.340	-0.90	6.31
Thriller	142	0.60	1.908	-0.93	16.41
War	11	0.14	0.896	-0.65	2.51
Western	1	-0.43			

CHAPTER 4

EMPIRICAL METHOD

Tacit collusion by its nature is very difficult to detect. This paper attempts to detect tacit collusion by comparing observed outcomes in the movie industry with an expected outcome of tacit collusion under an alternating-periods monopoly (APM). In a competitive environment, studios release similar films relatively close to one another or even on the same day. These films will compete for tickets sales and split the market demand. However, if studios are tacitly colluding the predicted outcome is that studios restrict output (produce fewer films) since they cannot collude on ticket prices, and, more importantly, space out the release dates of similar types of movies to reduce intratemporal competition. By spacing out releases of similar films, studios can enjoy monopoly-like market power during the period of time until the release date of a competing film.

Following Zillante (2005), I use duration analysis to look for evidence of a potentially collusive outcome. A hazard model is used to determine if film releases are spaced-out over time or clustered. Clustered releases provide evidence that studios are not colluding by APM and that the market is relatively competitive. Spaced-out releases provide evidence that studios may be tacitly colluding by following an APM strategy. The hazard function is defined as:

$$h(t) = \frac{f(t)}{1 - F(t)}$$

where *F(t)* is the distribution function and *f(t)* is its density function.

Positive duration dependence implies that the probability that a new movie release occurs is increasing in the time since the last competing movie release. Positive duration dependence means that studios are waiting to release their films; there is a higher probability that studios are spacing out releases and following an APM strategy. Positive duration dependence estimates a longer duration between the release dates of two similar movies. A longer duration period means that a film has monopoly-like market power for a longer period of time.

On the other hand, negative duration dependence implies that the probability of a new release is decreasing in the time since the last competing movie release. Negative duration dependence means that studios are clustering releases; there is a lower probability that studios are spacing out releases and are competing by clustering releases. Negative duration dependence estimates that release dates of similar movies are relatively close together. A shorter duration between release dates suggests that there is more head-to-head competition for ticket sales.

A Weibull distribution function is chosen because (unlike an exponential distribution function) it can exhibit increasing, decreasing, or constant duration dependence. The Weibull distribution function and its hazard function are:

$$P(t) = 1 - \exp(-\lambda t^{\alpha})$$

$$h(t) = \lambda \alpha t^{\alpha - 1}$$

where λ is the scale parameter and α is the shape parameter. The value of α ranges from zero to infinity. If α is greater than one, then the hazard function exhibits positive duration dependence, and the model predicts spaced-out releases. If α is less than one, then the hazard function exhibits negative duration dependence, and the model predicts clustered releases. If α equals one, the model predicts that movie releases are neither spaced-out nor clustered.

For each estimate of the shape parameter α, I order subsamples by release date. The duration of an observation is measured as the number of days between a film's release date and the release date of the next competing film released. Measuring duration in weeks (or months) does not affect the empirical results. In order to control for seasonal demand, I estimate the hazard model using dummy variables for holiday release, January release, and September release.

Several adjustments were made to the data regarding duration lengths. The release date is defined as the date in which a film opened in 900 theaters or more. Limited releases often open in fewer than 300 theaters, and even as low as one theater. Films opening in fewer than 900 theaters likely provide little competition against those opening in more than 900 theaters. This benchmark was chosen because the sample exhibited a natural break between limited releases and nationwide releases at 900 theaters.

Of the 755 films released during the sample period, 52 were originally released in fewer than 900 theaters. However, studios eventually expanded the theatrical release of these films to over 900 theaters. Therefore, the release date for these 52 films in the sample is determined by the date in which they were screened in at least 900 theaters since this is when their competitive duration begins.

In addition, I limit films' duration periods in several ways because long durations between observations can bias the estimate of α downward below one. Without limiting the duration length, small subsamples can incorrectly predict clustering of releases. A film's duration ends if one of the following events occurs: another similar film is released, the film's box office revenue falls below the top ten in a given week, the film is removed from theaters, the film earns less than $1 million in weekly box office revenue, or after twenty-eight days.

In most cases, a film's duration ended because either another film was released or the film fell below the top ten box office earners in a given week. Films earning less than $1 million per week generally have much lower theater counts and do not compete heavily against newer films. Restricting a film's duration to twenty-eight days is a relatively conservative cutoff duration because the average duration in the sample is twenty-four days. This is a reasonable constraint since a firm rarely remains a strong competitor more than one month after its release.

Finally, a hazard function will omit any movie with a duration of zero. Therefore, if two competing movies were released on the same day, I added 0.1 to the release date of one of the films. If three movies were released on the same day, then I added 0.1 to one of the films and subtract 0.1 to another one of the films. This keeps the measured duration close to zero without losing observations.

CHAPTER 5

RESULTS

Table 4 provides results of a robust test of whether the Weibull hazard function captures spacing out of films by narrowing the sample to the studios with the largest number of releases. Not surprisingly, I find evidence of positive duration dependence with all of the studios. Positive duration dependence ($\alpha > 1$) implies that studios are spacing out the releases of their own films. Sony released the largest number of films in the sample, and has a larger estimate for α than six other studios. This means Sony may have done a better job spacing out films than the other studios. DreamWorks has the highest estimate for α and did not release two films on the same weekend during the sample period. Paramount Pictures, which has the lowest estimate for α, released two films on the same weekend on three separate occasions.

Estimating a subsample containing the four studios that released the largest number of films illustrates a potential issue using duration analysis; too many observations estimate negative duration dependence ($\alpha < 1$). Stated differently, a large enough sample size will suggest that studios are clustering film releases. However, studios likely spaced-out films by specific characteristics like budget size and genre.

Table 4: Spacing Out Within Top Releasing Studios. Notes: The asterisks refer to significance levels for a two-tailed test for α=1. ∗∗∗ is significant at 1%, ∗∗ is significant at 5%, and ∗ is significant at 10%. The number of films in each row is its # durations + 1. Duration is measured in days. Rate of Return = (USBO-Budget)/Budget

Studio	α	Robust SE	# Durations	Avg. Duration	ROR
Sony & Columbia	2.247***	0.144	95	15.3	0.51
20th Century Fox	2.037***	0.179	88	14.8	0.50
Top 2 Film Releasers	1.177	0.120	184	9.2	0.50
Universal	2.076***	0.204	82	15.3	0.27
Warner Brothers	2.297***	0.276	78	16.7	0.47
Top 4 Film Releasers	0.673***	0.034	346	5.2	0.44
Disney & Buena Vista	2.770***	0.562	61	19.9	0.71
Lion's Gate	1.990***	0.251	58	14.2	1.93
Paramount Pictures	1.724**	0.386	52	17.1	0.40
New Line	2.725***	0.319	40	17.0	0.38
Weinstein & Dimension	2.439***	0.286	30	14.9	0.48
DreamWorks	2.921***	0.705	28	20.8	0.31
MGM & UA	2.219***	0.314	26	15.0	0.14
Focus Features	2.634***	0.589	18	16.8	0.53
Fox Searchlight	2.085***	0.269	16	14.0	2.60
Summit	2.290***	0.356	11	15.1	0.79
Miramax	2.538***	0.665	11	15.1	0.19

In Tables 5-9 I restrict the sample to examine what type of films studios spaced-out. Table 5 reports estimates that allow me to test if studios spaced-out or clustered film releases by budget size or by the number of theaters a film is released in during its first week. The results also illustrate that a subsample containing a large number of films estimate negative duration dependence and thus clustered releases. About 250 films were released with either a budget size of over $50 million or in 3,000 theaters. However, the results are not puzzling because even if studios perfectly spaced-out these films, one would be released about every week during the five-year sample period.

Table 5: Spacing Out by Budget and Opening Theaters. Notes: The asterisks refer to significance levels for a two-tailed test for α=1. ∗∗∗ is significant at 1%, ∗∗ is significant at 5%, and ∗ is significant at 10%. The number of films in each row is its # durations + 1. Duration is measured in days. Rate of Return = (USBO-Budget)/Budget

	α	Robust SE	# Durations	Avg. Duration	# Studios	ROR
Budget:						
≥ $50 million	0.778***	0.055	252	6.8	18	0.13
≥ $75 million	0.935	0.094	142	9.7	10	0.17
≥ $100 million	1.640***	0.136	80	13.7	7	0.17
≥ $125 million	1.821***	0.157	57	15.4	6	0.21
≥ $150 million	1.829***	0.228	44	17.3	6	0.23
Opening Theaters:						
≥ 3,000	0.871*	0.069	246	7.1	13	0.72
≥ 3,250	1.212*	0.120	142	11.1	9	0.72
≥ 3,500	1.664***	0.151	96	14.1	8	0.56
≥ 3,750	2.473***	0.302	47	18.9	7	0.65
≥ 4,000	3.070***	0.754	21	21.2	6	0.79

Once the sample is restricted to films with budgets over $100 million, and then again to films released in over 3,250 theaters, the results suggest that studios are spacing out releases. Although duration analysis tends to predict positive duration dependence as the sample size decreases, it is an unlikely coincidence that between seven and nine studios spaced-out expensive and widely released movies during the sample period. Studios have a larger incentive to space out releases of films with large budgets in order to recoup production costs.

The results in Table 6 indicate that studios spaced-out the release of sequels with either a budget larger than $25 million or a release in more than 2,000 theaters. However, the estimate for all sequels in the sample suggests that studios neither spaced-out nor clustered releases. The average budget for a sequel in the sample is $80 million, and this is 63% higher than the sample average. Since sequels have a built in audience studios have a large incentive to space out sequels from one another, especially because sequels are more expensive on average to produce.

Table 6: Spacing Out by Sequel, Budget, and Opening Theaters. Notes: The asterisks refer to significance levels for a two-tailed test for α=1. ∗∗∗ is significant at 1%, ∗∗ is significant at 5%, and ∗ is significant at 10%. The number of films in each row is its # durations + 1. Duration is measured in days. Rate of Return = (USBO-Budget)/Budget

Sequel	α	Robust SE	# Durations	Avg. Duration	# Studios	ROR
All Sequels	1.166	0.12	146	10.0	14	0.90
Budget ≥ $25 million	1.239**	0.129	115	10.8	13	0.29
Budget ≥ $50 million	1.331***	0.145	84	13.0	10	0.33
Budget ≥ $75 million	1.697***	0.135	65	14.6	8	0.32
Theaters ≥ 2,000	1.259**	0.130	136	10.8	13	0.90
Theaters ≥ 2,500	1.404***	0.150	121	11.5	11	0.88
Theaters ≥ 3,000	1.698***	0.155	98	13.1	11	0.84

Comparing the results in Table 5 and Table 6 show that the number of durations is higher and the average duration is lower in Table 6 than most of the estimates. This is important because it suggests that studios were able to space out a large number of sequels, and even avoid clustering all sequels released during the sample period. For example, ten studios were able to space out eighty-four films, each costing $50 million or more, by an average of about two weeks. Similarly, eleven studios were able to space out almost one hundred films, each released in over 3,000 theaters, by an average of almost two weeks.

The estimates for duration dependence by MPAA rating and for different subsamples by budget size and opening theaters for each rating are reported in Table 7. The results are very similar to those reported in Table 6; studios spaced-out releases for each MPAA rating by budgets over $50 million ($75 million for PG-13) and 3,000 opening theaters.

The highlight of Table 7 is the estimate for G-rated films. Studios only produced a total of twenty-five G-rated films during the five-year sample period. G-rated films have a relatively high estimate for α and a high average duration. In addition, the average budget for G-rated films in the sample is $59 million. This is 20% higher than the average budget of the entire sample. Studios collectively produced relatively few, but expensive, G-rated films and spaced-out the releases from another.

Table 7: Spacing Out by MPAA Rating, Budget, and Opening Theaters. Notes: The asterisks refer to significance levels for a two-tailed test for α=1. ∗∗∗ is significant at 1%, ∗∗ is significant at 5%, and ∗ is significant at 10%. The number of films in each row is its # durations + 1. Duration is measured in days. Rate of Return = (USBO-Budget)/Budget

MPAA	α	Robust SE	# Durations	Avg. Duration	# Studios	ROR
G	2.130*	0.852	24	19.8	6	0.81
PG						
Budget ≥ $25 million	1.203	0.155	104	12.1	16	0.21
Budget ≥ $50 million	1.767***	0.332	62	16.7	11	0.21
Budget ≥ $75 million	3.297***	0.638	40	21.7	8	0.28
Theaters ≥ 2,500	1.201	0.149	130	12.8	11	0.43
Theaters ≥ 3,000	1.658***	0.222	80	15.6	11	0.52
PG-13						
Budget ≥ $25 million	0.797***	0.062	216	7.8	17	0.26
Budget ≥ $50 million	1.125	0.125	128	11.5	12	0.17
Budget ≥ $75 million	1.616***	0.201	75	14.8	9	0.18
Theaters ≥ 2,500	0.914	0.078	208	7.9	16	0.52
Theaters ≥ 3,000	7.406***	1.247	108	12.5	12	0.59
R						
Budget ≥ $25 million	1.033	0.125	124	10.3	18	-0.10
Budget ≥ $50 million	2.067***	0.485	49	17.1	9	-0.10
Budget ≥ $75 million	5.075***	1.337	18	22.4	8	-0.16
Theaters ≥ 2,500	1.091	0.148	104	12.2	13	0.97
Theaters ≥ 3,000	1.875**	0.539	39	18.7	10	1.24

Table 8 and Table 9 report estimates of the duration dependence model by single-genre and common genre combinations. All but one of the common-genre combinations exhibit positive duration dependence (spaced-out releases). The category romance-comedy appears to be spaced-out despite having the largest number of releases, while the category drama-biography has the second lowest number of releases and does not appear to be spaced-out.

About one third of the single-genre categories exhibit positive duration dependence (spaced-out releases). Several of these genres have over seventy releases. However, two thirds of the single-genre categories exhibit constant duration dependence (neither spaced-out nor clustered releases). It is surprising that the four genres biography, music, science fiction, and war have forty or fewer releases, but do not appear to be spaced-out during the five-year sample period.

Table 8: Spacing Out by Single-Genre and Common-Genre Combinations - Statistically Significant. Notes: The asterisks refer to significance levels for a two-tailed test for α=1. *** is significant at 1%, ** is significant at 5%, and * is significant at 10%. The number a films in each row is its # durations + 1. Duration is measured in days. The total number of films for all genres sums to a number larger than the sample size because each film is categorized by up to four genres. Rate of Return = (USBO-Budget)/Budget

Genre	α	Robust SE	# Durations	Avg. Duration	# Studios	ROR
Animation	2.368***	0.444	53	18.9	8	0.34
Fantasy	1.425**	0.198	88	14.3	13	0.17
History	2.377***	0.415	19	16.8	8	-0.12
Horror	1.919***	0.282	78	13.9	14	1.44
Mystery	1.426**	0.203	77	13.9	13	0.87
Sport	1.845***	0.336	38	14.6	10	0.31
Action-Comedy	2.229**	0.665	31	18.3	11	0.58
Adventure-Action	1.763***	0.269	73	14.5	10	0.13
Adventure-Animation	2.498***	0.711	39	20.3	7	0.39
Drama-Action	2.041***	0.332	50	15.5	13	0.14
Drama-Comedy	1.344**	0.202	89	13.4	15	1.20
Drama-Crime	1.673***	0.227	79	13.3	13	0.55
Family-Fantasy	2.460***	0.483	22	18.2	7	0.01
Horror-Thriller	1.993***	0.401	50	14.2	11	1.57
Romance-Comedy	1.551***	0.182	98	13.6	16	0.77
Romance-Drama	1.405**	0.207	68	14.2	14	1.01
Comedy	0.667***	0.034	316	5.5	19	0.71
Drama	0.607***	0.025	341	5.2	19	0.71

The two broad genres comedy and drama exhibit negative duration dependence (clustered releases). These single genre categories contain so many films that predicting negative duration dependence is unavoidable. For example, nineteen studios released 342 dramas during the sample period. The average duration of dramas is less than a week. Even a perfectly spaced-out schedule of one film per week is more suited to be classified as clustered releases.

Most of the genres that exhibit positive duration dependence reflect the results from Tables 5-7. For example, animated and adventure-animated films are usually a combination of a G-rating, a large budget, and widely released in theaters. Adventure-action, drama-action, and action-comedy films tend to also have large budgets and wider theater releases. In addition, studios have an incentive to space out horror, horror-thriller, and drama-comedy films because the rates of return can be very high since the budget size is usually low. For example, the average budget size for horror movies in the sample is about $22 million, or 44% of the sample average. In addition, many horror and horror-thriller films are sequels or remakes.

Table 9: Spacing Out by Single Genre and Common Genre Combinations - Statistically Insignificant. Notes: The asterisks refer to significance levels for a two-tailed test for α=1. *** is significant at 1%, ** is significant at 5%, and * is significant at 10%. The number a films in each row is its # durations + 1. Duration is measured in days. The total number of films for all genres sums to a number larger than the sample size because each film is categorized by up to four genres. Rate of Return = (USBO-Budget)/Budget

Genre	α	Robust SE	# Durations	Avg. Duration	# Studios	ROR
Action	1.131	0.112	180	9.0	14	0.14
Adventure	1.058	0.111	162	9.6	15	0.27
Biography	1.357	0.380	27	16.1	10	0.45
Crime	1.110	0.121	140	9.4	15	0.54
Family	1.223	0.167	89	13.3	12	0.29
Music	1.186	0.275	36	13.8	11	0.80
Romance	1.081	0.119	134	11.4	17	0.79
Science Fiction	1.274	0.302	40	15.6	10	0.13
Thriller	1.106	0.130	145	9.6	16	0.60
War	1.299	0.640	10	15.4	8	0.14
Western	-	-	0	-	1	-0.43
Drama-Biography	1.357	0.380	27	16.1	10	0.45

CHAPTER 6

CONCLUSION

Alternating-periods monopoly (APM) is a relatively unexplored strategy that allows firms to collude tacitly. Amelio and Biancini (2010) believe that APM is more likely to be maintained with uncertain demand because it eliminates the information problem of detecting cheaters when firms decide to share a monopoly each period. However, the same point can be made in markets with seasonal demand like the film industry. Each year, studios have fifty-two weekends, including five major holidays, to space out release dates of similar types of films. Also, large-budget sequels tend to be released two or three years apart so the nature of production allows for turn-taking.

In addition, several factors that help facilitate APM can be found in the movie industry. First, studios are able to use large advertising campaigns to send signals to competitors and establish credible release dates. Second, the high cost of producing and marketing films reduces the incentive to release a film in every period. Third, studios' inventory cost is practically zero. Studios can finish a film and allow it to remain unscreened for several weeks or months while "waiting its turn." In the meantime, the people and resources involved in the film can move on to other projects instead of remaining idle.

Admittedly, detecting tacit collusion using duration dependence analysis does have limitations. Large samples inevitably lead to clustered release predictions. Also, running the hazard model with holiday, January, and September dummies adjusts for seasonal demand somewhat broadly. A method that weights each day of the year would be a more comprehensive adjustment for seasonality. For example, more releases in peak-demand periods may not exactly be considered "clustered" and fewer releases during low-demand periods probably should not be viewed as "spaced-out."

The results from the Weibull hazard model is suggestive of evidence that during the sample period of 2005-2009 studios likely tacitly colluded by spacing out releases of films with budgets exceeding $100 million, wide releases of over 3,250 theaters, sequels, or a G-rating. As expected, each studio spaced-out its own releases. The duration dependence estimates are consistent with a tacitly collusive outcome; as the stakes get higher through larger budgets, wider releases, and sequel status studios produce fewer films and space out releases.

Future research is needed to determine if APM can actually increase welfare in some markets like the movie industry. Zillante (2005) argues that APM may potentially improve welfare if consumers have a preference toward "newness." In some markets, consumers may prefer a continual stream of products rather than firms offering a glut of new products sporadically. Firms may also reduce the duplication of innovation costs by following an APM strategy. An important policy implication is that a collusive arrangement under APM can potentially make consumers better off.

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